

Intelligent Computing Methods in Medical Diagnosis

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Abstract

Disease diagnoses are a complex tasks in medical practice, especially for medical students and new apprentice staff. One of the most promising fields in bioinformatics is medical decision support system. Various artificial intelligent approaches are now being applied to enhance decision making of the clinicians such as using artificial neural networks, fuzzy logic, Bayesian networks, expert system and genetic algorithm. Numerous artificial intelligent techniques are integrated into hybrid intelligent medical informatics in order to produce most effective results in diagnostic tasks.

Key words: Bayesian networks, decision support system, diagnosis, fuzzy logic, hybrid intelligent system, medical, neural network.

1. Introduction

Nowadays, medical diagnosis is a complex task requiring accurate patient data, a deeply understanding of the medical literature and immense experience. In diagnosis process, the doctors deeply search for the cause (disease) to get the best explains of the symptoms for a

patient¹. The acquisition throughout narrat of the disease process is the first step in gather information. The information includes one severity, position, period, character and cou of the sign and symptoms being occurred by patient. Additional information regardi medical, social, and family histories is a needed. With this information, clinician c

start the process of formulating a list of potential diagnoses². The computer systems called decision support system (DSS) has been used to evaluate the most accurate diagnosis result.

Decision Support System (DSS) is defined as a combination, interactive computer software, including of analytical tools and information management capabilities, created to assist decision makers in solving unstructured problems³. In medical solving uncertainty problem, DSS is also contributing to enhance medical practice and health quality care such as clinical diagnosis⁴⁻⁶. Coiera⁷ classified the clinical decision support system (CDSS) based on the clinical tasks as follow: alert and reminders⁸, diagnostics assistance⁹, prescription decision support⁹, therapy critiquing and planning¹⁰, information retrieval, image recognition and interpretation¹¹, and diagnostic and educational systems¹².

Clinical decision support system (CDSS) has often been used to support medical practices in their diagnostic procedures, especially whenever there are problems of differential diagnosis in diseases¹³. The various techniques of artificial intelligence (AI) have the ability to formalize the expert knowledge and normalize numerous dissimilar diagnostic procedures in particular domains of medicine and store the expert knowledge in computer systems¹⁴.

This study covers the methods based upon intelligent computing methods (ICM) and their integrations. The ICM includes artificial neural networks (ANNs), fuzzy logic (FL), genetic algorithm (GA), and bayesian networks (BNs). The combination methods

include FL-ANNs, ANNs-GA, case-based reasoning with rule-based reasoning (CBR-RBR) and others. The BNs system and their integration model likes BNs and decision tree (BNs+DT), BNs and Multilayer perceptron (BNs+MP), and BNs with case-based in medical domain are also elaborated.

The paper has been divided into four sections. The First and Second Section introduce the scenario of ICM such as FL, NNs, GA and BNs in medical diagnosis. Third Section deal with various combined methods such as neuro-fuzzy systems (NNs-FL), rough sets and probabilistic neural network (RS-PNN), case-based reasoning and rule-based reasoning (CBR-RBR), case-based, fuzzy and genetic algorithm (CB-FL-GA), and others. Forth Section consists of the integrated BNs in medical applications. Final Section summarizes the conclusion of the study.

2. Intelligent computing method (ICM) :

A Modern approach authorized by Rusell *et al.*¹⁵ claimed that there were several methodologies in AI such as¹⁶⁻¹⁹ FL, NNs, GA and BNs. Methodology, technique, and approach are used interchangeably by several researchers in this field. These approaches have been applied in decision support systems (DSS) to assist humans in decision making tasks.

2.1 Artificial Neural Networks (ANNs) :

Dey *et al.*²⁰ elaborated ANNs as “connectionist architectures, parallel distributed processing, and neuromorphic systems, are systems where inputs are mapped to identify

outputs via weights during a training process". ANNs have been proven successfully ICM in pattern recognition engines and robust classifiers with the ability to formulate decisions about rough input data^{19,20}.

Lingaard *et al.*²¹ also mentioned that ANNs are well suited for predictive tasks,

whereas BNs effective y in diagnostic tasks. The argument made that bayesian algorithms presented a viable alternative for diagnosing the presence of a particular disease and thus for providing effective decision support in medical diagnostic DSSs²¹. Although ANNs has been successfully used in many areas of medicine as it has been illustrated in Table 1.

Table 1. ANNs-based medical systems and their applications

ANNs system	ANN model	Application/ Domain
CDSS ²²	Feedforward BP	Diagnosis and treatment in intensive care unit (ICU)
Lung cancer diagnosis ²³ system (LCDS)	algorithm (FANNC)	Diagnosis in lung cancer
Diagnosis system ²⁴	Rough sets (RS) and probabilistic neural network (PNN)	Diagnosis in breast cancer
Orthodontic system ²⁵	Feed-forward back-propagation (BP)	Diagnosis in orthodontic
DSS ²⁶	Multilayer perceptron (MLP)	Diagnosis in urology diseases
Radiographic ²⁷	Multilayer perceptron (MLP)	Diagnosis in proximal dental caries
Computer-aided intelligent diagnostic system (CAIDSA) ²⁸	Back-propagation neural network (BPNN)	Diagnosis in asthma
Expert system ²⁹	Combined neural networks (CNNs)	Diagnosis in erythematous-squamous diseases
ANNS ³⁰	Multilayer perceptron neural network (MLP), and back propagation algorithm (BP)	Diagnosis in diabetes
Expert system ³¹	Back propagation (BP)	Treatment in orthodontic,

Table 2. Fuzzy system with their application domains

Fuzzy system	Fuzzy technique	Application / Domain
Care plan on-line (CPOL) ³⁴	Fuzzy optimization	Treatment and planning in chronic care
ICU system ³⁸	Fuzzy logic algorithm	Treatment in intensive care unit (ICU)
Computer aided medical diagnosis (CAMD) ³⁵	Fuzzy cognitive maps and fuzzy logic	Diagnosis in clinical context
Prediction system ³⁹	Fuzzy inference	Diagnosis in head and neck cancers
Computer aided medical diagnosis (CAMD) ³⁵	Fuzzy cognitive map, fuzzy temporal reasoning and fuzzy logic	Diagnosis in differential disease
Medical decision support system (MDSS) ³⁶	Fuzzy cognitive maps	Diagnosis in language pathology, speech pathology, and obstetrics
HIROFILOS ⁴⁰	Fuzzy rules	Diagnosis and treatment in prostate diseases
Medical expert system ⁴¹ (MES)	Fuzzy temporal logic	Diagnosis in ICD10
Medical decision support ⁴² system (MDSS)	Fuzzy cognitive maps and fuzzy rule-extraction techniques	Treatment and planning in radiotherapy

The benefit of ANNs can be found in their flexibility against changes in the input data and their capability of learning. ANNs have been effectively used to merge inputs from multiple sensors for tool condition monitoring²⁰. ANNs are black-box models that well suit for pattern recognition, for example in medical image analysis³². However, ANNs need a lot of training data to perform well and is less suitable for the development of clinical classification and prediction models⁴. The truth that clinical data are often uncompleted and modeled relations are unidentified and, therefore, not readily understood or explained. ANNs is not suitable

approach in the case of insufficient data⁴.

2.2 Fuzzy Logic (FL) :

Second ICM is fuzzy set theory. It was formerly introduced by Lotfi Zadeh in the 1960s and simulate human reasoning in its use of inexact information and improbability to generate decisions²⁰. One of major advantage of FL algorithms over ANNs or BN is FL algorithms are easy to construct and revise²¹. In recent years, researchers have done many surveys related to implementation of fuzzy technology in medicine and healthcare^{17,33}.

Several fuzzy techniques deployed in medical application such as fuzzy optimization³⁴, fuzzy cognitive maps^{35,36}, and fuzzy temporal logic³⁷. A few of the applications with fuzzy techniques was summarized in Table 2.

2.3 Bayesian Networks (BNs) :

The word BNs frequently refers to a belief network which are more strictly related to expert systems than ANNs and do not

necessarily involve learning⁴³. ANNs is commonly applied for predictive tasks whereas BNs is immensely applied in diagnostic tasks²¹. A Bayesian algorithm showed a possible choice for diagnosing the existence of a particular disease. Lingaard *et al.*²¹ also supported that BNs are effectively applied for decision support in medical diagnostic DSSs. Table 3 shows the BN systems with their specific features and medical domain.

Table 3. Bayesian networks system with their application domains

Bayesian networks	Reasoning / specific features	Application / Domain
Medical decision ⁴⁴ support system (MDSS)	Causal probabilistic network (CPN) formalism	Diagnosis, prediction (prognostic) and treatment selection in ICU
ISABEL ⁴⁵	Diagnostic was provided by the associated text description, relevant images, national guidelines, and clinical experiences	Diagnosis in pediatric,
PROMEDAS ¹	Large causal probabilistic network	Diagnosis in anaemia,
DSS ⁴⁶	Knowledge and uncertainty were represented in the form of a Bayesian belief network	Diagnosis in preinvasive cervical squamous (PCS)
Computer-assisted diagnosis (CAD)	Breast imaging reporting and data system descriptor (BI-RADS)	Diagnosis in breast cancer
DSS ⁴⁸	Naive bayes classifier. System automatically detects diseases given a description (a set of manifestations) of a retinal image	Diagnosis in retinal diseases
DSS ⁴⁹	Bayesian network classifiers	Diagnosis in breast cancer
Bayesian DSS ⁵⁰	Decision tree (reference diagnosis)	Diagnosis in ventilator-associated pneumonia
Intelligent DSS ⁵¹	Bayesian classification models	Diagnosis in embryo selection
DSS ⁵²	BN prognostic model	Treatment and planning in endodontic

3. Hybrid Intelligent Systems (HIS) :

Various integrated ICM are applied in medical problems such as neuro-fuzzy systems (NN-FL), rough sets (RS) and probabilistic neural networks (RS-PNNs), case-based reasoning and rule-based reasoning (CBR-RBR), feed forward back-propagation artificial neural networks (FP-ANNs) and k-nearest neighbor (k-NN), principal component analysis (PCA), artificial immune system (AIS) and

fuzzy k-NN. Single ICM have its own advantages and disadvantages as described in Section 2. The disadvantages of the single ICM can be removed by integrating various ICM approaches. The integrated intelligent methods also supported the user to get a better result to a problem, compared to using a single method for the same problem¹³. Table 4 presents the integrated methods with specific features used in medical system.

Table 4. Integrated medical systems and their application

Integrated method	Systems	Specific features	Application /Domain
Linear programming and ANNs	DIA ⁵⁴ (DSS+CAMD)	Integrated knowledge information base (KiB) with the inference properties of a data evaluator	Diagnosis in pulmonary diseases (PDs)
Knowledge-based (KB) and data-based (neural networks)	EMERGE-DSS ⁵⁵	Knowledge-based system that used symbolic reasoning. Neural networks model that derived knowledge through supervised learning. Time series analysis that summarized biomedical signal analysis data.	Diagnosis in cardiac disorders and evaluation of dementia
Neuro-fuzzy systems (NNs-FL)	DSS ⁵⁶	Generic self-organizing fuzzy neural networks (GenSoFNNs) with truth-value restriction (TVR) fuzzy inference, as a fuzzy DSS (denoted as GenSo-FDSS) for the classification of all subtypes using gene expression data.	Diagnosis and treatment in pediatric cancer
Rough sets (RS) and probabilistic	Diagnosis ²⁴ System	Rough sets to reduce redundant attributes from a biomedical	Diagnosis in breast cancer

neural networks (PNNs) (RS-PNNs)		dataset.Used probabilistic neural network to perform final supervised classification task.	
Principal component analysis (PCA), artificial immune system (AIS) and fuzzy k-NN	Expert system (ES) ⁵⁷	An expert system based on principal component analysis, artificial immune system and fuzzy k-NN for diagnosis of valvular heart diseases	Diagnosis in valvular heart diseases
Case-based reasoning and rule-based reasoning (CBR-RBR)	CDSS ⁵⁸	Able to tackle problems like high complexity, low experienced new staff and changing medical conditions	Diagnosis in ICU
Fuzzy logic-neural networks (FL-ANNs)	ES ⁵⁹	Fuzzy expert system of diagnosing. Adaptive neural networks fuzzy system	Diagnosis in hepatitis-B,
Case-based, fuzzy and genetic algorithms (GAs).	DSS ⁶⁰	Case-based data clustering method and a fuzzy decision tree for medical data classification Genetic algorithms (GAs) are applied to construct a decision-making system based on the selected features and diseases identified.	Diagnosis in breast cancer; classification of liver disorders
Feed forward back-propagation artificial neural networks (FP-ANNs) and k-nearest neighbor (k-NN)	Intelligent System ⁶¹	Hybrid intelligent techniques for MRI brain images classification	Classification of MRI brain images

Table 5. Integrated Bayesian networks

Integrated components	Bayesian systems	Application / Domain
BNs+ Decision tree	DDSS ⁶⁵	Diagnosis and treatment
BNs+ Multilayer perceptron (MP)	BNA ⁶⁶	Classification of ovarian tumor
BNs+FL	ES ⁶⁷	Classification and diagnosis in cardiology
BNs+NNs+Decision Tree	AptaCDSS-E ⁶⁸	Diagnosis in cardiovascular disease (CVD)
Bayesian + CB	CASESIAN ⁶⁹	Treatment in medical prescription

Many advantages of NN-FL in medical applications were demonstrated by researchers^{53,62}. Tung *et al.*⁵⁶ found that the combination of NNs-FL is able to produce diagnosis result in high accuracies. Three reasons were found to support the powerful of NNs-FL in ICM. First, NN-FL is capable to present the extracted knowledge and explicate the computed solutions to the end users; second reason is having a logical reasoning process that is as good as to the individual reasoning process; and lastly, is able to integrate new knowledge with current information in the computer program.

Integration of CBR-RBR simplifies knowledge acquisition, improve efficiency and accuracy, improve performance and decrease competence gap⁶³. Kumar *et al.*⁵⁸ integrated a CBR and RBR in a DSS for domain independent clinical decision support in intensive care unit (ICU) to achieve a better solution and result.

4. Hybrid Bayesian Networks (HBNs) :

The hybrid of ICM could reduce medical diagnosis system from lack of generality, limited learning capability, lack of generic reasoning mechanism, and lack of systematic guidelines in the design⁶⁴. Therefore, many studies have been reviewed in hybrid bayesian with other ICM to resolve the drawbacks. Table 5 shows bayesian systems integrated with others ICM in their applications.

5. Discussion and Conclusion

In this study, the framework of integrating BNs inference and case-based CDSS for diagnosing oral and maxillofacial pathology (OMP) is proposed (see figure 1). OMP is the "specialty of dentistry and pathology which deals with the nature, identification and management of diseases affecting the oral and maxillofacial region. It is a science that investigates the causes,

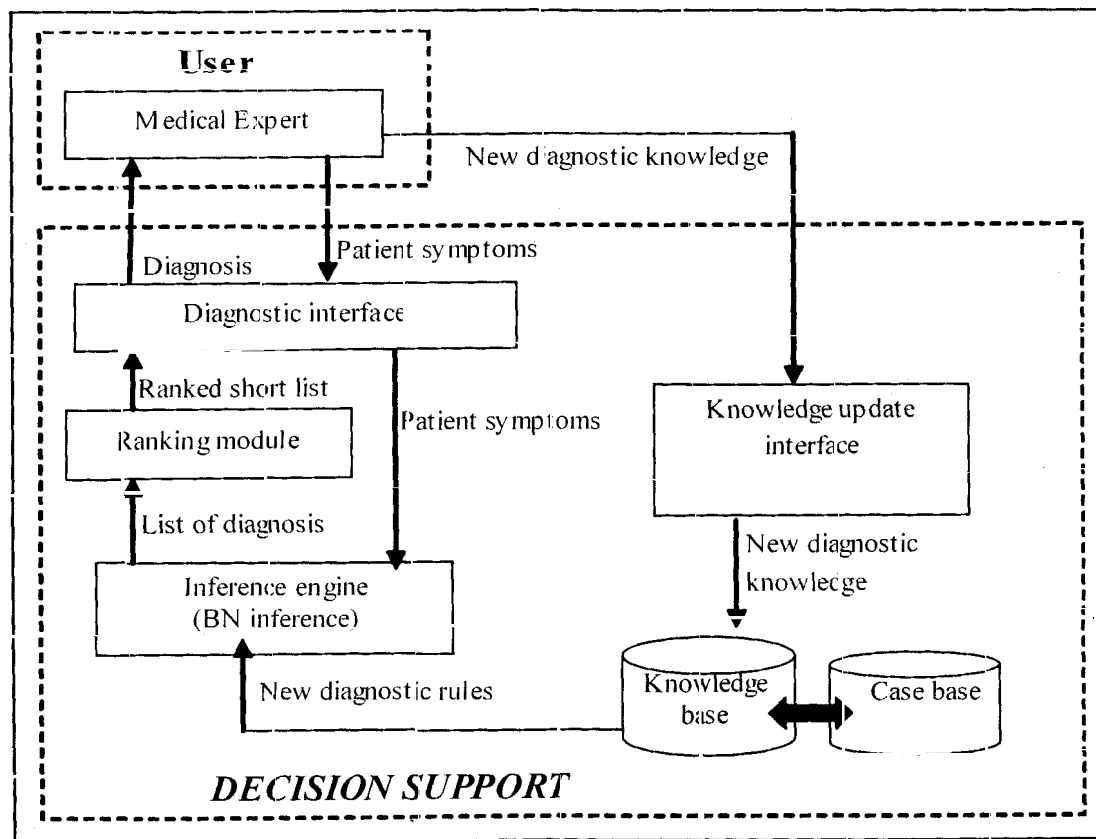


Figure 1. Framework of proposed Hybrid Bayesian network CDSS for diagnosing OMP

processes and effects of these diseases. The practice of oral and maxillofacial pathology includes research, diagnosis of diseases using clinical, radiographic, microscopic, biochemical or other examinations, and management of patients^{39,70}.

Variety of ICM method have been applied to achieve more accuracy in decision making tasks such as ANN, FL, BN, and CBR, to name a few. The integration of ICM methods are also applied to reduce the weaknesses of

single ICM and to improve the quality of decision making tasks. It was observed that ICM are more widely used in the medical diagnosis of various diseases, rather than their treatment and planning.

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